Equity Concerns in Infrastructure Financing: The Gas Tax vs. Vehicle Miles Traveled Fees

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ABSTRACT

Estimation of a discrete choice model allows for the correction of selection bias that results from including vehicle information in the demand specification for the continuous choice of miles traveled. Utilizing separate elasticities for different income levels and household characteristics, this paper estimates how a switch to a national vehicle miles traveled (VMT) fee system would alter tax incidence and consumer welfare. Revenue neutral VMT fees are calculated for each state and at the federal level. It is found that although each jurisdiction has the ability to set a revenue neutral fee on its own, doing so can have a negative impact on the other jurisdiction. Consistent with prior studies, the 2001 National Highway Transportation Survey (NHTS) suggests that a VMT fee would be more regressive than the gasoline tax; however, utilizing the same model, the 2009 NHTS indicates that a VMT fee would be less regressive, likely due to changes in fuel efficiency and vehicle holdings patterns. Consistent with previous studies, retired persons and those in rural areas would benefit the most from a VMT system.

INTRODUCTION

The gasoline tax is employed as an excise tax at both the state and national level in order to provide funding for transportation infrastructure development and maintenance. For a variety of reasons, the present funding mechanism is becoming increasingly unsustainable. Due to the gasoline tax not varying with the price of gasoline nor being indexed to inflation, the amount being transferred to the National Highway Transportation Fund (NHTF) per mile driven has been decreasing in real terms steadily since the last time the tax was increased. The Government Accountability Office included funding the nation's surface transportation system as one of 30 high risk areas in its 2013 report to congress (1), where it has been included since 2007. Another factor that threatens the long term feasibility of utilizing excise taxes on gasoline as a stable funding mechanism is the increasing fuel efficiency of the nation's automobile fleet. According to the Bureau of Transportation Statistics (2), new vehicle fuel efficiency improved from 28.8 miles per gallon (MPG) in 2001 to 33.8 MPG in 2010 for passenger cars. New light trucks saw a similar increase from 20.9 MPG to 25.2 MPG over the same period. These increases are dramatic relative to the previous ten years. Continually increasing requirements from the Corporate Average Fuel Economy (CAFE) standards aim to increase fuel efficiency of passenger cars to 35.5 MPG in 2016 and 54.5 MPG in 2025. These commitments are aimed at reducing greenhouse gas emissions and dependence on foreign oil, and could save consumers money on gasoline; however, they also serve to further undermine the NHTF, as vehicles will be doing more damage to roads per gallon of gasoline consumed. Combine this with the inability of congress to agree on a long term transportation finance bill, and the result is a desire to find alternative mechanisms to fund highway development and maintenance in the future.

According to a recent report by the Congressional Budget Office (CBO, 3), "at the end of 2012, the total obligated amounts of contract authority in the highway account were equal to about two years of collections of excise taxes." A series of short term measures, in the form of increasingly large transfers from the general fund of the treasury, which have totaled $44 billion since 2008, have kept the NHTF afloat. The current funding, known as Moving Ahead For Progress in the 21st Century (MAP-21, Public Law 112-141) will expire on September 30th, 2014. It is projected that the NHTF will require another $14 billion from the general fund in 2015 to avoid a shortfall. Furthermore, all but 4.3 cents of the federal fuel tax is set to expire in

2016. The CBO estimates that without spending cuts, taxes on motor fuels will have to be raised by about 10 cents per gallon in order to meet current obligations.

Due to the political infeasibility and potential inequity that would result from increasing the gasoline tax, many states are investigating the potential options to increase transportation funding in a way that will be more equitable. Some possible solutions include toll roads, including those run by private entities, and per mile fees, often referred to as vehicle miles traveled (VMT) fees. Schweitzer (4) provides a recent review of empirical research on the equity implications of various transportation funding mechanisms. A recent working paper by Miller (5) looks at political implications of different funding mechanisms, arguing for the consideration of transitioning towards a decentralized VMT fee system, possibly through privatization.

The goal of this study is to provide a consistent comparison of the distributional effects of instituting a VMT fee, including tax incidence and other welfare measures. The next section reviews literature relevant to the present inquiry; section III details the model used; section IV describes the data; section V compares results to those obtained in previous studies; section VI concludes.

LITERATURE REVIEW

The focus of this review is on studies relevant to estimating the welfare effects of instituting a vehicle miles traveled (VMT) fee. While the overall impact on society is likely to be similar to the current structure (6), there could be considerable heterogeneity in how the tax burden is distributed based on income and other demographic characteristics. Since no known studies on VMT equity have controlled for selection bias or endogeneity, some related literature utilizing these techniques in similar contexts is also reviewed.

Distributional Effects of a VMT Fee

Several studies have attempted to estimate the distributional effects of various VMT fee structures, utilizing a variety of methods and measures. These studies rely on a specification that estimates the demand for miles driven in response to the price per mile. The consensus is that a VMT fee would be regressive, meaning that those with a lower income would pay a larger proportion of their income in tax under the structure than those with higher incomes; however, since most assume that a VMT fee would replace rather than supplement the current gas tax, the concern is whether a VMT fee would be *more* regressive than the current gasoline tax. Most recent studies on this issue have used the 2001 and/or 2009 National Household Transportation Survey (NHTS), with older studies more likely to use the annual Consumer Expenditure Surveys (CEX) administered by the Bureau of Labor Statistics (BLS).

Zhang et al. (7) analyzed a subset of 3,581 households from the 2001 NHTS, estimating the short-run and long-run impacts of a VMT fee. The short-run model is estimated using ordinary least squares (OLS), including a variable to indicate whether a household can substitute between types of vehicles to drive and a variable indicating the number of vehicles owned. This model suggests that VMT is more regressive than the gasoline tax, but that rural households will benefit from the VMT structure at the expense of urban households. They find that lower income households would lose consumer surplus, while higher income households would gain it. Their long-run model appends the NHTS data with vehicle prices and weights from the 2001 *Ward's Automotive Yearbook* and the *Internet Auto Guide,* respectively. They estimate separate models for vehicle number, and vehicle combinations, using weight to classify vehicles as either cars or trucks. They do not use the results of the vehicle choice models to explicitly control for endogeneity. Their long-run results indicate that rural households will actually be worse off, although they conclude that the redistributive impact of the VMT fee structure is negligible compared to those resulting from long-run fluctuations in the price of gasoline. A subsequent study (8) used OLS and the same data, but looked at only Oregon households, and concluded that a VMT fee would be slightly more regressive than the gas tax.

Weatherford (9) used the national representation of the same data (NHTS 2001) to estimate the effects of a 0.98 cent per mile VMT fee at the national level, and found that a VMT fee structure would redistribute the tax burden from those who are retired to younger households and from rural households to urban households, while 98% of households would see a change of less than $20 annually. The overall elasticity found in this study, -1.48, is very large relative to empirical estimates. His subsequent dissertation (10) is one of the only known studies to use the 2009 NHTS, pooling it with the 2001 version. While his estimate of the average price-elasticity of demand for miles is over 1 in absolute value with each dataset alone, for the pooled data it is -0.42. The results suggest that a flat-rate VMT fee is neither more nor less regressive than the gas tax, but that a VMT fee would lower the burden on retired people and those in rural areas.

Modeling Vehicle Choice and Usage Sequentially to Control for Endogeneity

It is well established in the literature that in order to obtain an accurate estimate of the response to a change in the cost of driving, it is necessary to model the choice of vehicles as well as vehicle utilization, since each can influence the other (11, 12, 13, 14, 15). The omission of this correction is one of the limitations of most recent studies. The exact method to control for endogeneity typically depends on the type of data being used. It is common for studies with aggregate data to utilize 2 Stage Least Squares (2SLS) or 3 Stage Least Squares (3SLS), while those using micro-level data have traditionally utilized some variant of the methods outlined in Dubin & McFadden's seminal paper (16). This section will review literature pertaining to the estimation of vehicle choice and usage with the Dubin-McFadden method, as it is necessary to use micro data to establish welfare impacts.

Mannering and Winston (11) were the first to adapt the Dubin-McFadden model to vehicle choice and usage. They utilized data from the Household Transportation Panel and the National Interim Energy Consumption Survey (NIECS) for 1977-1980 to investigate changes in vehicle ownership and utilization resulting from the 1979 energy crisis, concluding that it would have a small effect on gasoline consumption and vehicle use. Their method included using a multinomial logit to estimate the discrete choice of vehicle ownership, utilizing the resulting probabilities in place of dummy variables in the estimation of the vehicle utilization equation.

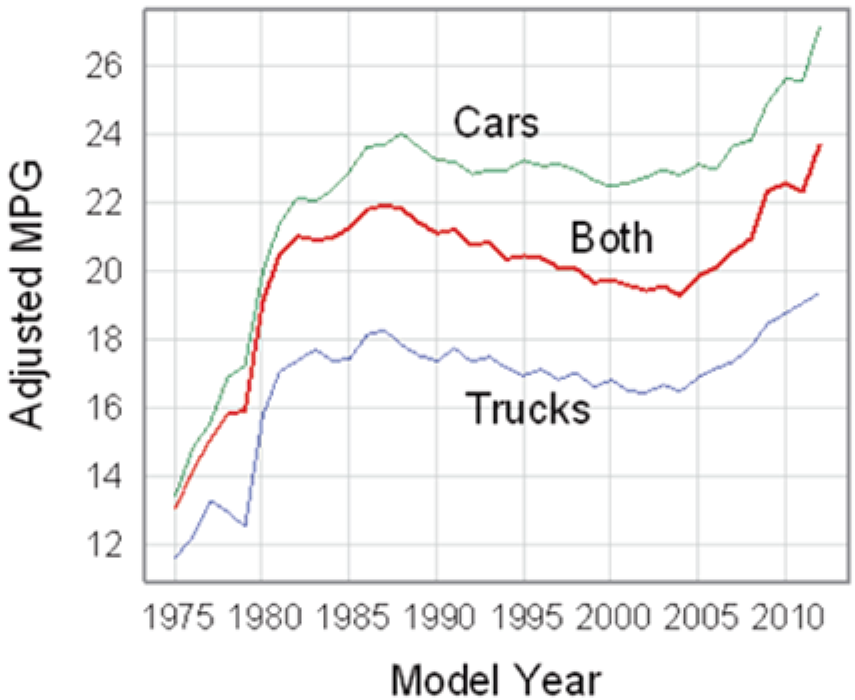
Train (12) utilized a sequentially estimated nested logit structure to estimate the discrete choice of vehicle type from the 1978 National Transportation Survey. By estimating the relationship between household characteristics and the average operating cost of vehicles in different nests, he was able to add additional information to the discrete choice estimation while avoiding additional bias due to endogeneity that would result from using the actual demand for miles for each household. He corrected for endogeneity of vehicle choice in the continuous estimation of vehicle utilization by using the instrumental variable method rather than the conditional expectation method used in most studies, which entailed creating instruments for per-mile operating costs. He reports an elasticity of about -0.28 for one vehicle households, and an insignificant elasticity for households with two vehicles.

West (13, 14), using data from the 1997 CEX, considers welfare effects of a VMT fee while controlling for endogeneity of vehicle choice resulting from vehicle selection. She makes the important distinction that the results of most studies looking at incidence should be interpreted as the incidence for vehicle owners, and not for the population as a whole, since most datasets do not contain households without vehicles. Following the methodology of Dubin & McFadden (16), she utilizes a conditional expectation correction approach to correct for selection bias (13). The elasticity of VMT with respect to price-per-mile is estimated for each income quintile, which enables her to calculate the change in consumer surplus and taxes paid for both vehicle owners and the population as a whole. Her results indicate that, of vehicle owners, those in the lowest income decile have a price elasticity of -1.46, with price elasticities decreasing monotonically to -.77 for those in the 8th decile. This would seem to indicate that those with lower incomes should be better able to avoid the tax by substituting other travel modes in the long-run, but the overall welfare impact would depend on what activities they had to give up to do so. Her work does not consider any possible feedback effects between VMT and the price per mile. While she compares the equity implications of the gas tax to those of an emissions fee, she does not look at the possibility of a mileage charge replacing the gasoline tax.

A recent dissertation (15) applied the same approach as to the 2001 NHTS dataset, appended with data on vehicle prices and annual service miles of public transportation available in each CMSA/MSA. The main finding is that while the elasticity of demand for miles in low transit areas resembles the pattern found by West (14), the opposite pattern is found for households in high transit areas and for households with vehicles in general. She does not compare the regressivity of a mileage fee to an increase in the per gallon excise tax.

As of now, no known studies have compared the welfare impacts of per mile fees to excise taxes utilizing estimates obtained by applying the Dubin-McFadden ‘Conditional Expectation Correction Method’ to the most recent 2009 NHTS data. A major limitation of the studies that have explicitly looked at welfare impacts of switching to a VMT fee is that they do not explicitly correct for selection bias. Selection bias is important to consider, as its presence can lead to biased and inconsistent estimates. In addition, the existing literature has had conflicting results with respect to the regressivity of a VMT fee relative to the gas tax (7, 8, 9, 10, 17). It is important to see if these confounding results are due to a structural change or an artifact of estimation procedures. Due to the trends in vehicle fuel efficiency (see Figure 1), it is possible that the distributional effects could be considerably different now than as estimated in studies using older data.

FIGURE 1 Historical Average Fuel Economy.



Source:United States EPA (18)

DATA

The main sources of data are the 2001 and 2009 National Highway Transportation Survey, which include information on household vehicles, including make, model, and year, as well as household demographic characteristics such as income, household size and number of workers. The datasets also include variables on miles driven, gasoline cost, and vehicle miles per gallon (MPG).

The NHTS data was appended with data on vehicle operating costs taken from the *Transportation Energy Data Book* (19), which is published annually by the Oak Ridge National Laboratory. This included the annual fixed costs of operating a vehicle based on vehicle year, as well as the per-mile costs of tires and maintenance. Also included in this data was average depreciation based on vehicle year, which was turned into a depreciation rate using the average vehicle price for vehicles sold that year. Since previous studies (13, 15) have noted a close relationship between vehicle prices and annual maintenance, additional data on the price of new vehicles was taken from the 1985-2009 *Ward's Automotive Yearbook*s (20). Ward's publishes these books annually, which contain characteristics of each vehicle on the market in a given year. The simple average of the highest and lowest priced options for each model were calculated and used to determine annual depreciation for each vehicle based on the average annual depreciation rate for a given year. The vehicle price data was merged with the NHTS data based on the FARS make and model code provided in the dataset after extracting the names from the *2009 NASS (FARS) Vehicle Makes and Models* (21) publication available as part of the user's guide to the 2009 NHTS on the ORNL website. The addition of this vehicle specific data allows for the estimation of a discrete choice model, which is critical to controlling for selection bias.

In order to run regressions on the household level data, some observations had to be removed from the merged dataset. Due to the NHTS having only one category for older vehicles, the analysis was limited to households owning vehicles that were produced no earlier than 1985. Observations which had a vehicle make or model that was not produced in the year provided in the dataset were dropped, as well as observations that did not have recorded values for income, miles driven, or gas cost. In addition, any observation that corresponded to a heavy truck or alternative means of transportation, such as a motorcycle, golf cart, etc., were not included in the regression.

In order to run discrete choice models, household vehicle holdings had to be separated into different categories. In total, 118,021 of the initial 150,147 households remained in the 2009 NHTS after eliminating observations with missing data. In the 2001 NHTS, of the 26,038 households, a total of 19,109 have sufficient data. Following previous studies (13, 15), trucks, vans, and SUVs were grouped together and classified as trucks. A household with two or less vehicles could have one car, one truck, two cars, two trucks, or a truck and a car, with each classification having three age categories. A household with three or more vehicles could have three of the same class of vehicles or a mixture of cars and trucks. The newest vehicle owned by the household was the bases for the vintage classification for households with less than three vehicles. Table 1 summarizes the age and types of vehicles for 5 different income ranges, as a percentage of all vehicles owned by that income group based on the 2009 data. Over 35% of the households in the lowest income category own a single vehicle with a vintage between 1985 and 1999, compared to less than 5% of households with an income over $100,000. As income increases, households are more likely to own newer vehicles and are more likely to have multiple vehicles.

TABLE 1: Vehicle Holdings by Household Income (Percent)							
		Household Income					
Vehicle Combo	**Year of Newest Vehicle**	Less than $25,000	$25,000 to $49,999	$50,000 to $74,999	$75,000 to $99,999	More than $100,000	**Full Sample**
Car	**1985-1999**	26.04	10.93	5.21	3.70	2.57	**9.49**
	2000-2004	16.64	13.14	8.11	6.01	4.70	**9.87**
	2005-2008	8.49	9.18	7.27	5.42	5.32	**7.3**
Truck	**1985-1999**	11.11	5.84	3.44	2.48	1.55	**4.83**
	2000-2004	7.95	7.92	6.90	5.93	5.16	**6.83**
	2005-2008	4.13	5.73	5.90	5.37	5.75	**5.44**
Two Cars	**1985-1999**	1.46	1.36	1.18	0.99	0.73	**1.15**
	2000-2004	1.58	2.96	3.51	3.75	3.94	**3.16**
	2005-2008	1.28	2.80	4.44	5.05	6.64	**4.03**
Two Trucks	**1985-1999**	1.18	1.11	0.73	0.56	0.30	**0.79**
	2000-2004	1.75	3.38	4.20	4.47	2.96	**3.33**
	2005-2008	1.38	3.67	5.79	7.51	8.06	**5.21**
Car and Truck	**1985-1999**	3.15	3.01	2.28	1.54	1.03	**2.24**
	2000-2004	3.97	7.15	8.62	8.47	7.51	**7.17**
	2005-2008	3.07	7.06	10.99	13.08	15.76	**9.93**
Three or More Vehicles		6.88	14.75	21.42	25.68	28.03	**19.21**
Percent of Sample		16.82	27.50	19.02	14.85	21.81	
Total Observations		19,854	32,456	22,451	17,525	25,735	**118,021**

Data on state and federal excise taxes were taken from the December 2001 and 2009 Monthly Motor Fuel Reported by States published by the FHWA Office of Highway Policy Information (22, 23). These were used to calculate tax incidences for each income category and to calculate revenue neutral VMT fees to replace the gasoline tax for each state.

MODEL

The conditional expectation correction method was applied to each dataset to estimate the elasticity of miles with respect to the price-per-mile for each household, which were used to calculate tax incidence and changes in consumer welfare. This approach consists of sequentially estimating vehicle choice and utilization, utilizing the probabilities of a household selecting each vehicle bundle to calculate correction terms to be used as explanatory variables in the estimation of the demand for VMT (12, 13, 16). Barrios (24) showed that the expected probabilities from any RUM model can be used to form a selection bias term similar to that found in Dubin & McFadden (16). This corrects for selection bias resulting from the fact that household miles are only observed for vehicles they have selected to drive, as well as the endogeneity of vehicle combo choice indicators that occurs when unobserved factors influence both choices. The model presented below is most similar to the work of West (13), although it has elements from other models which allow for more heterogeneity (7, 9).

In discrete choice models that are consistent with Random Utility Maximization (RUM), it is assumed that the chosen alternative is the one with the highest overall utility; i.e. a household will choose to own the bundle of vehicles (b) for which:

$$U_b > U_j \quad for\ all\ j \neq b$$

The corresponding probability of choosing a given bundle is:

$$P_b = Prob(U_b > U_j \quad for\ all\ j \neq b)$$

Since it is not possible to observe the actual utility function of a household, it is necessary to use an approximation based on observable factors, which is known as representative utility (25). The following is the probability of choosing bundle b:

$$P_b = Prob(V_b + \varepsilon > V_j + \varepsilon \quad for\ all\ j \neq b)$$

The assumption made about the distribution of ε determines which discrete choice model is being used. Logit models utilize the extreme value distribution, which allows for closed form solutions, while probit models utilize the normal distribution and typically involve simulation. Mixed logit models are a generalization of these two types of models in which the error term is a mixing distribution.

Several discrete choice models were estimated and compared in order to find the best fitting model. A mixed logit model can approximate any other discrete choice model, including nested logit (26). This model is desirable because it relaxes the Independence from Irrelevant Alternatives (IIA) hypothesis embodied in multinomial and nested logit models, and is always consistent with utility maximization. In addition, mixed logit models can allow increased heterogeneity in preferences through random coefficients, and can allow these coefficients to be correlated. Traditional mixed logit models assume that random parameters follow a normal distribution, although in practice any mixing distribution can be used to supplement the extreme value distribution that is assumed for the fixed parameters. Latent class models, which are essentially mixed logit models with a discrete mixing distribution, were also estimated, and were found to fit the data much better. Latent class models allow for variation between different unobserved classes, but not within. Consistent Akaike's Information Criterion (CAIC) and Bayesian Information Criterion (BIC) were used to determine the best fitting model between various specifications of mixed logit and latent class models. These measures take into account the tradeoff between goodness of fit and the number of parameters.

The probability of selecting a particular bundle in the latent class model can be calculated by taking the weighted average of the traditional logit probability formula with the coefficients estimated for each class:

$$P_{nb} = \sum_{c=1}^{C} S_c \left(\frac{e^{b_c' x_{nb}}}{\sum_j e^{b_c' x_{nj}}} \right)$$

where the weights (S_c) are the estimated probability household n falls into class c, x_{nb} are observed characteristics of bundle b, x_{nj} are observed characteristics of other bundles, and b_c' is a vector of the estimated coefficients.

It is likely that unobserved factors are correlated with both the choice of vehicle bundle and the demand for miles, which would cause biased estimates due to selectivity. Using the probabilities from the discrete choice model, it is possible to calculate a selection bias correction term for each household of the form (17, 23):

$$\sum_{j \neq b} E\left(\frac{P_{nj} \ln(P_j)}{1 - P_j} \right) - E(\ln(P_b))$$

This term is included as an explanatory variable in the estimation of the demand for VMT by each household. The final equation used for the estimation of demand for miles is:

$$\begin{aligned} \ln(VMT_b) = {} & \alpha \ln(income) + \gamma \ln(cost/mile) + \gamma \ln(cost/mile) * income \\ & + \beta_j \ln(cost/mile) h_j' + \beta_k h_k' + \beta_{state} \\ & + \left[\sum_{i \neq b} E\left(\frac{P_i \ln(P_i)}{1 - P_i} \right) - E(\ln(P_b)) \right] + \eta \end{aligned}$$

Household demographics may affect the response to a price change. The term h_j' includes household specific factors found to interact with the price-per-mile, which allow for the household response to a price change to vary across households over factors other than the household's income. The term h_k' includes household specific factors that have a direct impact on the demand for miles. State fixed effects, β_{state}, are also included to control for unobserved factors within each state that affect driving behavior.

Calculating a Revenue Neutral VMT Fee

Previous work has tended to measure the impact of a change at either the state or federal level. Due to the interaction between miles traveled and tax revenue, such decisions are not mutually exclusive. Initial results suggested a net loss in revenue for the federal and state governments if both follow their "individually rational" revenue neutral fee without taking into consideration the behavioral adjustment due to the price changes resulting from adjustments to the other jurisdiction's policy change.

From the perspective of each state, a revenue neutral fee would be calculated by setting current revenue equal to the per mile fee multiplied by the number of miles driven after the change. Since households will either increase or decrease their demand for miles depending on their relative burden under the current system and their elasticity per mile, each state must consider the aggregate of each individual as follows:

$$\sum_{i=1}^{n} t_{s_0}^{g} gallons_{i_0} = t_s \sum_{i=1}^{n} miles_i$$

Where $t_{s_0}^{g}$ is the initial per gallon excise tax for the state, $gallons_{i0}$ is the initial annual gallons consumed by individual i, n is the number of people in state s, t_s is the new per-mile tax for the state, and $miles_i$is the annual miles driven by individual i after the tax change. Since the miles driven after the tax change depend on the initial miles driven and the price-elasticity of miles driven, in addition to the change in the tax rate:

$$\sum_{i=1}^{n} t_{s_0}^{g} gallons_{i_0} = t_s \sum_{i=1}^{n} miles_{i_0}(1 + \varepsilon_i(\%\Delta\, price_m))$$

Typically the midpoint formula would be used to calculate the change in price per mile. However, using the initial price as the base allows for a simple solution by turning the problem into a quadratic equation. In each sample, this approximation leads to an increase in total revenue of about 25 cents, which is quite small. It can be shown that the fee that solves this equation under these circumstances is:

$$t_s^* = \frac{\sum_{i=1}^{n}\left[\left(\frac{(t_{s_0}^{g})gallons_{i_0}}{p_{i_0}}\right)\varepsilon_i - miles_{i_0}\right] + \sqrt{\left(\sum_{i=1}^{n}\left[miles_{i_0} - \left(\frac{(t_{s_0}^{g})gallons_{i_0}}{p_{i_0}}\right)\varepsilon_i\right]\right)^2 + 4\left[\sum_{i=1}^{n} t_{s_0}^{g} gallons_{i_0}\right]\left[\sum_{i=1}^{n}\left(\frac{\varepsilon_i}{p_{i_0}}\right) miles_{i_0}\right]}}{2\left[\sum_{i=1}^{n}\left(\frac{\varepsilon_i}{p_{i_0}}\right) miles_{i_0}\right]}$$

This will achieve (almost) revenue neutrality as long as the federal government doesn't change the gas tax. Otherwise, in the presence of an effective change in the federal tax per mile, the problem becomes:

$$t_s^* = \frac{\sum_{i=1}^{n}\left[\left(\frac{(t_{s_0}^{g} + t_{f_0}^{g})gallons_{i_0}}{p_{i_0}}\right)\varepsilon_i - \left[1 + \varepsilon_i\left(\frac{t_f}{p_{i_0}}\right)\right] miles_{i_0}\right] + \sqrt{\left(\sum_{i=1}^{n}\left[\left[1 + \varepsilon_i\left(\frac{t_f}{p_{i_0}}\right)\right] miles_{i_0} - \left(\frac{(t_{s_0}^{g} + t_{f_0}^{g})gallons_{i_0}}{p_{i_0}}\right)\varepsilon_i\right]\right)^2 + 4\left[\sum_{i=1}^{n} t_{s_0}^{g} gallons_{i_0}\right]\left[\sum_{i=1}^{n}\left(\frac{\varepsilon_i}{p_{i_0}}\right) miles_{i_0}\right]}}{2\left[\sum_{i=1}^{n}\left(\frac{\varepsilon_i}{p_{i_0}}\right) miles_{i_0}\right]}$$

The problem for the federal government would be similar, and can be found by swapping t_s and t_f. Initial results suggest that there is not a steady equilibrium to this set of equations. Every time a state adjusts their fee there is a change in federal revenue, and hence an incentive to change the federal fee. This becomes a massive coordination problem involving every state and the federal government.

It is possible to solve for a VMT fee for each state that brings in revenue equal to the total of all state and federal revenues. Essentially, this requires replacing t_s with $t_s + t_f$ in the equation for the individually rational state. In essence, this could either be a centralized system in which the federal government reallocates tax revenue to each state based on their current revenues, or it could be administered as a revenue neutral fee at the state level and differential federal fees by state. This revenue neutral fee is used in this study, and actually results in a lower tax per mile for each state than the average under the current system.

RESULTS

Table 2 shows the results of latent class models for different numbers of classes and their corresponding information criterion. The model with the lowest CAIC and/or BIC value is said to be closest to the “true” model. It is evident that the model including 10 latent classes, or unobserved segments of the population, is the best fit for each of the years.

TABLE 2: Information Criterion Results of the Latent Class Models

		2001 NHTS			2009 NHTS		
Classes	**Nparam**	**LLF**	**CAIC**	**BIC**	**LLF**	**CAIC**	**BIC**
2	36	-51143	102681	102645	-290821	582099	582063
3	58	-49891	100418	100360	-279347	559430	559372
4	80	-48373	97622	97542	-275726	552466	552386
5	102	-47603	96324	96222	-278090	557473	557371
6	124	-47312	95982	95858	-276540	554652	554528
7	146	-46170	93939	93793	-278649	559149	559003
8	168	-46658	95156	94988	-277579	557288	557120
9	190	-46949	95979	95789	-275865	554138	553948
10	**212**	**-45500**	**93323**	**93111**	**-271320**	**545328**	**545116**
11	234	-46737	96036	95802	-275974	554914	554680

Nparam: number of parameters; LLF: value of the likelihood function at convergence; CAIC: Consistent Akaike's Information Criterion; BIC: Bayesian Information Criterion.

Elasticities were estimated based on income and other demographics. It is evident that households with higher income tend to have a smaller response to price changes, although there is considerable heterogeneity within higher income households, depending on the age of their newest vehicle and whether they own a truck. Elasticities decrease monotonically with income, which is consistent with previous literature. The overall elasticity for the 2001 sample when correcting for selection bias is -1.10, while the overall elasticity for the 2009 data is -0.81 using the same model. The 2009 results are consistent with studies using a similar method (13, 25). As in West’s estimation, the overall bias corrected for by including the selectivity terms is small but significant. The elasticities for the 2001 data range from -2.01 to -0.42, which is rather large. Previous studies using this dataset have also found a larger range (9). The elasticities for the 2009 data range from -1.65 to -0.04.

TABLE 3: Regression for Natural Log of Annual Household Miles

Variable	2001 Coefficient (Bootstrapped SE)	2009 Coefficient (Bootstrapped SE)
ln(cents/mile)	-1.211 (0.081)***	-1.111 (0.027)***
ln(cents/mile)*(number of workers)	0.063 (0.042)	0.07 (0.014)***
ln(cents/mile)*sub	0.038 (0.09)	0.354 (0.03)***
ln(cents/mile)*trucks	0.192 (0.079)**	-0.119 (0.027)***
ln(cents/mile)*rural*retired	-0.407 (0.131)***	-0.159 (0.035)***
ln(cents/mile)*ln(income)	0.092 (0.052)*	0.111 (0.018)***
ln(cents/mile)*new	0.078 (0.068)	0.2 (0.023)***
sub	-0.141 (0.023)***	-0.076 (0.008)***
ln(income)	0.232 (0.012)***	0.231 (0.004)***
ln(employment density)	-0.043 (0.004)***	-0.05 (0.002)***
ln(employment rate)	0.051 (0.016)***	0.021 (0.003)***
number of workers	0.055 (0.011)***	0.106 (0.004)***
number of drivers	-0.009 (0.012)	0.045 (0.004)***
male	0.169 (0.011)***	0.097 (0.004)***
age	-0.004 (0.000)***	-0.006 (0.000)***
education	0.018 (0.003)***	0.025 (0.025)***
rural	0.068 (0.017)***	0.055 (0.007)***
retired	-0.11 (0.021)***	-0.095 (0.007)***
old	-0.309 (0.042)***	-0.235 (0.015)***
medium	-0.056 (0.026)**	-0.069 (0.009)***
R-Squared	0.237	0.289

1

Standard errors were bootstrapped with 5000 repititions to account for the 2 step estimation procedure. Results for selection bias correction and state effects not shown

TABLE 4: Average Annual Consumer Surplus Change based on Location and Whether Retired ($/HH)

	Household Income	Rural			Urban			Full Sample
		Retired	Working	Total	Retired	Working	Total	
2001								
	$5,000 to $24,999	-1.46	-21.74	-12.15	1.26	-18.49	-9.96	-10.61
	$25,000 to $49,999	17.47	-3.77	2.12	5.82	-15.72	-8.38	-5.43
	$50,000 to $74,999	24.20	13.28	15.12	6.90	-8.98	-6.34	-1.03
	$75,000 to $99,999	2.37	1.12	1.25	-2.22	-9.48	-8.62	-6.61
	More than $100,000	14.71	27.37	25.87	7.06	8.41	8.27	11.15
2009								
	$5,000 to $24,999	7.80	-1.77	4.08	5.69	-2.34	-2.45	2.99
	$25,000 to $49,999	10.55	-3.26	3.64	3.95	-4.13	-0.01	1.15
	$50,000 to $74,999	9.84	-3.67	0.83	7.47	-4.49	-0.17	0.14
	$75,000 to $99,999	13.45	-1.16	2.36	4.71	-5.74	-3.01	-1.40
	More than $100,000	5.04	-2.41	-0.90	7.22	-4.71	-2.38	-2.00

Welfare Impacts with Respect to Income and Other Demographic Factors

The welfare impacts were calculated for the 2001 and 2009 NHTS datasets using the sequentially estimated model with the Generalized Dubin-Mcfadden correction based on the latent class logit model. When looking at the tax incidence of the gasoline tax (table 3), it is apparent that lower income groups have acquired more fuel efficient vehicles, as they are paying a lower percent of their income in fuel taxes.

Results suggest that on average, households that have a retired person living within them, particularly in rural areas, would benefit. There is considerable heterogeneity within each of the income levels, with standard deviations ranging from 88.09 for the lowest income households to 158.83 for those households with the highest income. Those of working age in rural areas have the smallest standard deviations, while homes with retired persons in urban areas have the lowest. Nonetheless, the majority of drivers in each income level would benefit. The 2009 data shows a reversed pattern with respect to the change in consumer surplus compared to earlier studies based on the 2001 survey. Households with lower incomes would gain, while those with higher incomes would pay more. The average change for each group is less than five dollars; however, the standard deviations are considerably lower for those with lower incomes, indicating that the heterogeneity in impacts is lower. Those who drive the most miles would tend to pay more. These households tend to have higher incomes and own more vehicles.

TABLE 5: Distributional Effects Based on Miles Driven

	Total Household Miles (Annual)	Gas Tax/Income	Revenue Neutral VMT Fee/Income	Change in Consumer Surplus ($/HH)	% of HH benefitting	Average Number of Vehicles Per Household
2001						
	Less Than 7,500	0.38%	0.36%	6.16	62%	1.4
	7,500 to 14,999	0.70%	0.69%	6.37	52%	1.6
	15,000 to 24,999	0.93%	0.94%	0.71	50%	2.0
	25,000 or More	1.62%	1.67%	-19.77	48%	2.5
2009						
	Less Than 7,500	0.33%	0.29%	9.24	68%	1.3
	7,500 to 14,999	0.60%	0.57%	10.77	58%	1.6
	15,000 to 24,999	0.72%	0.71%	7.08	55%	2.0
	25,000 or More	1.22%	1.27%	-23.73	50%	2.6

CONCLUSION

Those with more fuel efficient vehicles are likely to be better off under the current system, as they use less fuel per mile. Earlier data, such as the 2001 NHTS, suggest that high income households would benefit the most from a switch to a mileage fee; however, this is likely due to the downward trend in the fuel economy of new vehicles that occurred between 1988 and 2004. Households with higher incomes are much more likely to own new vehicles. This trend is likely to continue, and with CAFE standards set to increase the fuel efficiency of newer vehicles drastically over the next decade, this means that these households will be able to further reduce their tax burden unless the system changes. In addition, households with retired persons and households in rural areas would tend to benefit the most from a switch to a VMT fee structure.

Overall, the sequential estimation pioneered by Dubin and McFadden (16) seems to lead to slightly lower estimates than OLS would without controlling for selection bias. The results, with an average elasticity of -0.81 are consistent with previous work utilizing this methodology (13). It should be noted, however, that West's elasticity estimates represented the elasticity of miles driven with respect to total operating costs, which included maintenance and tires. The model utilized in this study estimated this elasticity with respect to fuel cost per mile instead, which is consistent with other studies (28, 29). This doesn't seem to be a contradiction, as the price of gas increased much faster than inflation between the time when the 2009 NHTS and the data used in these studies was collected. The average total operating cost per mile for households with vehicles in West (13) is 10 cents per mile, which, adjusted for inflation, would have been 13.67 cents in 2009. The average price per mile in the 2009 NHTS dataset that is used is 15.55 cents.

Future work could look further into the interaction between state and federal tax policies with respect to transportation, particularly what will occur if both jurisdictions adopt VMT fees. An important consideration is what the general equilibrium effects of such changes would entail. It is also important that future studies consider the feedback between fuel efficiency and miles travelled, as this could lead to endogeneity beyond that occurring from selection bias.

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